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Optimal load scheduling for off-grid photovoltaic installations with fixed energy requirements and intrinsic constraints

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ABSTRACT

Solar energy is one of the most promising green energy sources. On-grid photovoltaic installations supply energy to consumers as a support energy source, but in isolated areas, it comes as the unique source. The decision-maker must dimension the installation, maintaining system performance with reasonable investments. In some scenarios, the utility manager can handle the energy delivered to consumers as every subsystem can be independently connected. A strategy for scheduling the energy consumption to decrease the number of photovoltaic modules required in a standalone system is proposed here. The problem formulation corresponds to generalising a more specific problem before published. We presented a real case study being the groups of hydrants that provide water to crops in a pressurized irrigation system for energy consumption to schedule.

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1. INTRODUCTION

Photovoltaic (PV) systems have increased in the last times, covering fields with limited applications. But, in productive activities, the PV panels installation is large capital expenditures that can reduce the incomes and increase the payback period making it unaffordable. Then, procedures for the optimal design of photovoltaic plants are necessary. Typical approaches to the design problem are based on the guarantee of energy under the worst case. Special development of research has emerged around hybrid installations as PV-diesel (Xue, 2017) or PV-ES (energy storage) plants (Dufo-López and Bernal-Agustín, 2005; Kaldellis et al., 2010; Perez, E.; Beltran, H.; Aparicio, N.; Rodriguez, 2013). Design of big plants are defined by their problems and has also been an object of study in (Beltran et al., 2012).

Solar energy production becomes one of the hottest topics in the water industry as irrigation occurs in isolated areas (no grid connection) and pressurized irrigation networks (PINs) are very energy hungry. For the last 70 years, irrigation networks shifted from gravity-fed irrigation into pressurized irrigation (PIN). The irrigated area grew 2.5 times, water consumption doubled and energy expenditure multiplied by 19 in Spain (Corominas, 2010). These enormous figures show efficient management of PIN has become of paramount importance (Moradi-Jalal and Karney, 2008; Pardo et al., 2018).

Given that the anthropic pressure influences the environment, the photovoltaic (PV) technology incorporates in the agriculture industry, like green (no emissions) and profitable choice to conventional power sources (Mérida García et al., 2019). Solar power management comes from one of the trendiest questions in the water industry (Aliyu et al., 2018; Chandel et al., 2015). Energy production in PV systems expanded overall energy production from 29.5 (2012) to 107 (2018) GW (Jäger-Waldau, 2019). This momentum is because of a shift to better large-scale service systems, shifts in legislation, and a universal devaluation of PV modules prices (Goodrich et al., 2013) (30–60% in 10 years; (Closas and Rap, 2017)).

Many researchers analysed how to convert direct-drive pumping devices fed by electricity grids into a standalone (off-grid) direct solar waterpower system (SPWS) (Betka and Attali, 2010; Elkholy and Fathy, 2016; Mohanty et al., 2018; Pardo et al., 2020a; Ru et al., 2013). Converting water pressurized network (WPN) into a standalone full PV supplied system involves accumulating energy in head tanks or batteries. But, in irrigation, the utility manager may regulate water (not in urban WPNs) and energy expenditure (Pardo et al., 2018). Standalone systems are the most widespread solution around the world because of simplicity, great efficiencies and adaptable to all sizes and irrigation methods (Hartung and Pluschke, 2018). Other optimisation problems have significant interest and an inherent difficulty, as determining the best tilt angle on locations under high diffusive and reflective factors (Gökmen et al., 2016; Kerekes et al., 2012). Design problems in extreme conditions involve considering other restrictions as cooling needs (Karira et al., 2004).

Scheduling problems to minimise (or maximise) an objective function by satisfying some set of constraints is frequently studied. To name a few, there are scheduling jobs in machines (Liu and Yang, 2011; Luo and Chu, 2006; Pham et al., 2007), transportation (Forouharfard and Zandieh, 2010; Shrivastava et al., 2002; Thengvall et al., 2003), computer task scheduling (Chrétienne, 1989; Feitelson et al., 1996; Moore, 2004, 2003) and energy optimising (Ahmed et al., 2017). These optimisation problems are hard to solve because of the size of the configuration space. By example, the job shop problem (JSP) (Fang et al., 1996; Gholami and Zandieh, 2009; Hefetz and Adiri, 1982; Koonce and Tsai, 2000; Nakano and Yamada, 1991) is known as an example of NP-complete problems (nondeterministic polynomial time).

The proposed algorithms to solve scheduling problems are non-deterministic (Forouharfard and Zandieh, 2010; Liu and Yang, 2011; Luo and Chu, 2006; Pham et al., 2007; Shrivastava et al., 2002; Thengvall et al., 2003), (Fang et al., 1996; Gholami and Zandieh, 2009; Hefetz and Adiri, 1982; Koonce and Tsai, 2000; Nakano and Yamada, 1991). For instance, genetic algorithms (Fang et al., 1996; Gholami and Zandieh, 2009; Nakano and Yamada, 1991; Shrivastava et al., 2002) are suitable for optimisation problems where the space of configuration is too big to be explored using a deterministic algorithm in workable computing time, or where the objective function presents local extremes. But the algorithm does not guarantee to get the global best solution to the problem (a limiting characteristic).

The present paper considers a case of the scheduling problem. It corresponds to the design of a photovoltaic (PV) installation where PV panels supply electricity to feed a pumping device in a pressurised irrigation network. In this approach, the irrigation network runs as a standalone SPWS and we intend to quantify the effect of selected schedule in a rigid rotation predetermined scheduled PIN (Replogle and Kruse, 2007).

The irrigation network complies a set of devices (hydrants, units and subunits) constrained to have a fixed time of operation. Two more requirements apply. The first is fixed operation time (water delivered to crops in every consumption node must be similar) but we can divide this period into intervals. The second is that the power consumption of the set of devices can depend on the connected appliances (nodes with high elevation far from the pumping system need more energy supplied by the pumping system).

For a set of devices with given shared consumption profiles, we parametrised the problem with the working times (hydrants opened supplying water to crops) and the number of intervals in which the day is divided. We have presented a restricted version of this problem (Pardo et al., 2018) applied to water pumping systems. We determine the optimal job scheduling to decrease the number of required solar panels for the power supply installation by the number of simultaneous devices (Q) and the number of time-slices (N). In (Pardo et al., 2018), we solve the problem by exploring the space of allowed combinations, composed by $Q \cdot 2^N$ configurations. But this method is not useful for big cases because of its dependence on the parameters Q and N. We develop a genetic algorithm to find the schedule minimise differences between the aim and the real injected flows (Pardo et al., 2020b). This earlier approach shows that it is impossible to calculate the $Q \cdot 2^N$ combinations. The present paper exploits a property of the feasible solutions that reduce the subset of the configuration space that is admissible as a solution. The fastnumerical algorithm developed in this investigation guarantees the solution with a computational complexity of $O(Q)$.

The rest of the paper is organised as follows. Section 2.1 exposes the problem and section 2.2 presents the basis of solar irradiance and clear sky models. Section 2.3 shows the objective function to minimise and 2.4 presents the formulation of the problem; Section 3 shows the case study where to solve the problem and Section 4 presents the solution for the optimal size design problem. and the discussion about the research. Finally, Section 5 highlights the conclusion.

2. MATERIALS AND METHODS

2.1. Problem exposition

Let us consider the problem of designing a PV plant for supply d devices in several states (connected or powered off would be the simplest case), numbered from zero (powered off) to S:

$$s \in \{0,1,..S\} \tag{1}$$

Let call each one of the allowed combinations a system configuration, represented by the d-dimensional vector ζ:

$$\zeta = \left\{(s_1,..,s_d)\middle|s_i \in \{0,1,..S\}\right\} \subset N^d. \tag{2}$$

Where S^d combinations may appear. Each with a power consumption function given by $c(\zeta)$.

Let us consider a work schedule for the devices of a determined system corresponding to a day. With different needs on different days, we would realise the

143 overall process for each day. If we divide the day into N slices, $\{t_1, t_2, .., t_N\}$, with size

144 Δ=24/N, there will be $S^{d \cdot N}$ possible daily combinations for the system. We show a working

145 plan example in Table 1.

	WORKING PLAN FOR 6 DEVICES																		
	8:00	8:30	9:00	9:30	10:00	10:30	11:00	11:30	12:00	12:30	13:00	13:30	14:00	14:30	15:00	15:30	16:00	16:30	17:00
DEVICE 1																			
DEVICE 2																			
DEVICE 3																			
DEVICE 4																			
DEVICE 5																			
DEVICE 6																			
Power demand	P_{1}	P_{1}	P_{12}	P_{12}	P_{125}	P_{1235}	P_{2345}	P_{2345}	P_{345}	P_{345}	P_{345}	P_{345}	P_{4}	P_{4}	P_{24}	P_{234}	P_{236}	P_{36}	P_{36}

Connected device   Disconnected device

Table 1: Working plan for 6 devices with slices of 30 minutes.

146 A working plan is then, a set of states associated with the group of slices,

147 $\Pi = \{\zeta(t_k)\}_{k=1}^{N}$. Given a working plan, it is possible to calculate the total power

148 consumption and time of operation:

149 $$P = \sum_k c\big(\zeta(t_k)\big). \quad (3)$$

150 $$T = \Delta \cdot \sum_{i,k} Ind\left(\xi^i(t_k)\right), \quad (4)$$

151 where $Ind(x)$ is the indicator function defined as:

152 $$Ind(x) = \begin{cases} 1 & x \neq 0 \\ 0 & x = 0 \end{cases}. \quad (5)$$

153 Also, representing by $E(t_k)$ the maximum power for generation by one PV panel

154 at a time t_k, the number of panels needed at this time is:

155 $$n(t_k) = \frac{c(\zeta(t_k))}{E(t_k)}. \quad (6)$$

156 And the number of panels needed by a working plan is:

$$\eta = \max_{k \in [1,N]} \left(n(t_k) \right). \quad (7)$$

A power-time representation of a working plan is a plot of the function c(ζ(t)) as Figure 1:

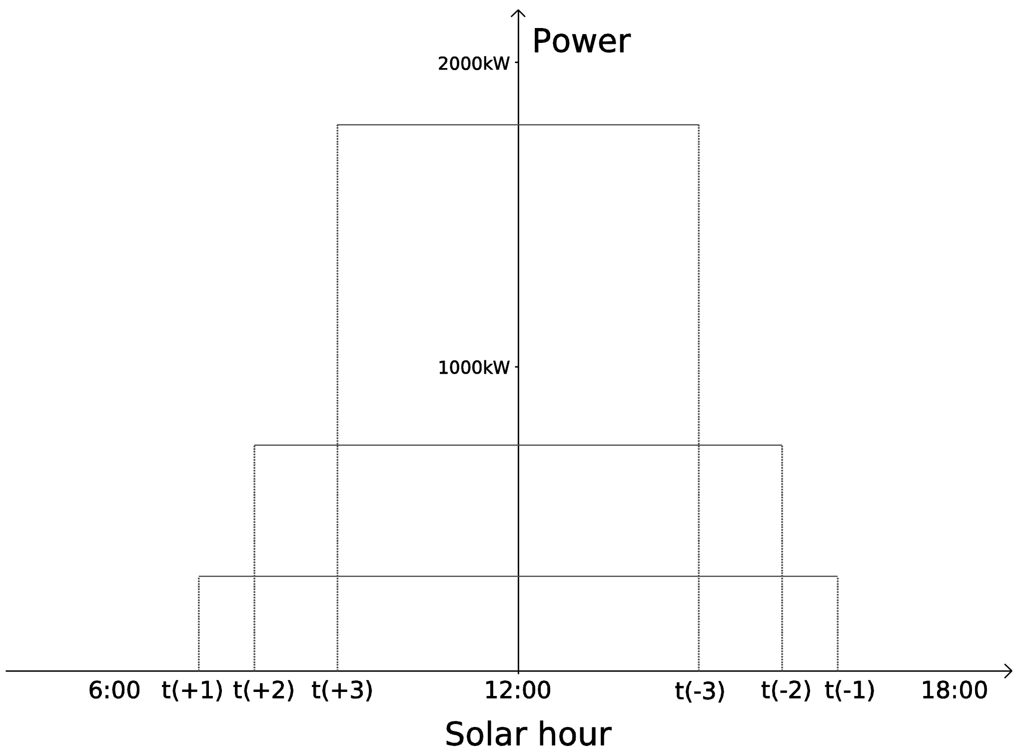

Figure 1. Power-time representation of a working plan

2.2. Model of maximum hourly solar irradiance

2.2.1. Basis of hourly solar irradiance

Let us introduce briefly some concepts and terminology that will be needed in the rest of the paper (for a more in-depth discussion see (Badescu, 2014; Cao and Lin, 2008; Page, 2012; Wald, 2018)).

The irradiance E is the power received per area (Watt per square meter). To calculate solar irradiance at ground level the first step is to consider its value on a normal horizontal surface at the top of the atmosphere (E_{0N}), and the value corresponding to a horizontal surface situated in the same point E_0, given by:

$$E_0 = E_{0N} \cdot cos(\theta_s), \tag{8}$$

where θ_s is the solar zenithal angle, related to the latitude of the point (Φ) and the declination of the sun (δ) through the equation:

$$cos(\theta_s) = sin(\Phi) \cdot sin(\delta) + cos(\Phi) \cdot cos(\delta) \cdot cos(\omega), \tag{9}$$

where ω is the hour angle measured from the local meridian to the position of the sun at each instant. Introducing the reduced time coordinate t, with t=0 at solar noon, the hour angle can be written as:

$$\omega = \frac{\pi}{12} \cdot t. \tag{10}$$

Let consider a panel facing south with an inclination given by the angle β (tilt) concerning the horizontal. The angle of incidence of the solar rays can be obtained as a modification of the expression (9):

$$cos(\hat{\imath}) = sin(\Phi - \beta) \cdot sin(\delta) + cos(\Phi - \beta) \cdot cos(\delta) \cdot cos(\omega). \tag{11}$$

From equation (11) the energy of the incident direction will have an expression:

$$E_{lin}(t) = A + B \cdot cos\big(\omega(t)\big). \tag{12}$$

The atmosphere affects the values calculated before because of light scattering causes the dispersion of light around the incident direction (depending on the wavelength). Then, the effective energy received at ground depends on the amount of atmosphere that must be crossed.

Also, the radiation that is reflected on the ground can impact in the solar panel contributing to the generated power. At ground level, the total irradiance is the sum of radiation that comes directly from the direction of the sun (direct or beam radiation), radiation originated by scattering processes in the atmosphere (diffuse radiation) and the radiation coming from the ground (albedo), a fraction of the total radiation that falls upon it (reflected radiation).

But even if we perform the calculations using all the precision, some factors scape from the equations and must be determined in situ (for instance, influence from the local topography in the values of the albedo). Moreover, the randomness of nature appears in the form of clouds or other meteorological elements that break the validity of the forecast.

We calculate here the least number of PV panels required to feed the energy demand using a curve of hourly power generation representative of the set of panels used in the installation calculated with the Duffie and Beckman equations (Duffie and Beckman, 2013).

2.2.2. Clear sky models

Equation (12) only considers the effect of direct radiation, but as we introduced previously, several other contributions determine the total power. The light beam is dispersed following a three-dimensional angular distribution around the direction given by the direct beam, and part of the energy arrives at the panel in angles different from that given by (12). Inclusion and calculation of diffuse irradiance is not a simple problem (see (Behar et al., 2015) for a comparison of the models).

The problem of determining the maximum irradiance available at any determined instant is studied using a class of models called clear sky models. Clear sky models complement equation (12) considering the contribution of incident beams with direction different from the direct one.

There exist a great variety of clear sky models, as can be seen in [59, 60]. Each model considers different dispersion terms, but a common characteristic of these terms is that they depend on the amount of atmosphere traversed by the light. A measure of this distance is the parameter called air mass, which depends on the zenithal (or equivalently the solar elevation) angle, related through equation (9) with the hour angle. For elevation angles greater than 20-30 degrees, the value of air mass can be considered constant. It is for smaller angles that the different models predict different values. However, the final behaviour is similar in the most of models, that is a reduction concerning considering only the direct beam given by (12) of irradiance at solar noon and an increment of the generated power for earliest and latest moments of the day. As a result, the power generated by the panel changes respect to the direct component as it is shown in Figure 2.

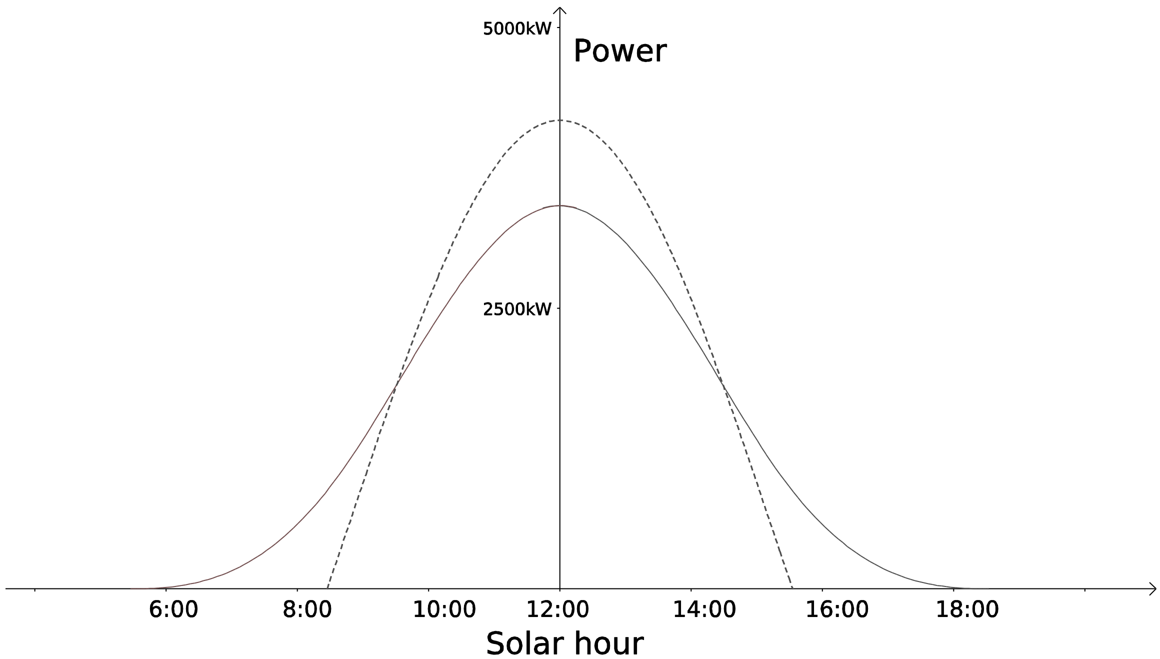

Figure 2. Models for the power generation of the PV panel. The dotted line corresponds to the direct beam, while the continuous curve represents the result when the diffusion component is included. The difference is exaggerated to show the effect.

An example is the Kasten–Czeplak model, given by the equation:

Kasten–Czeplak: $G_c = A \cdot cos\theta_z + B.$ (13)

where G_c is clear sky global radiation.

2.3 Objective function

Let us consider now the solution to the problem introduced in Section 2.1. Given the equations (6) and (7), the difference between them can be considered a measure of the under- or oversizing of the plant for a required power load, so an objective function can be defined as:

$$f(n_1, .., n_N) = \sum_{k=1}^{N} (\eta - n_k)^2, \quad (14)$$

where $(n_1, .., n_N)$ are the number of panels used in each interval and η is optimum.

Then, the optimal condition over is given by the null partial derivatives:

$$\partial_i f = 2 \cdot \sum_{k=1}^{N} (\eta \quad - n_k) \cdot \delta_{ki} = 0, \tag{15}$$

for every index i, so the solution is:

$$n_1 = n_2 =..= \eta. \tag{16}$$

That is, the optimum is got when the number of required panels is the same at every time, so the problem is to schedule a balanced load on the system, modifying the working plan to obtain a constant ratio between the load and the available power at each instant under the time operation constraint T.

2.4. Optimization Algorithm

At any time, the number of active devices varies from 0 to Q (if there is no constraint over the simultaneity in device working, this number would be the number of devices d). Depending on the vector ζ the consumption can vary, so let introduce

$$\pi_{(q)} = \min \; c(\zeta), \text{ where } \sum_i Ind\left(\xi^i(t)\right) = q. \tag{17}$$

Additionally, the problem is characterized by two different regimes of power demand. At the first and last hours, the demand determines the need for power, but in the central hours, the power generated exceeds the system needs. So, the optimization problem is determining the connection $t_{(+q)}$ and disconnection time $t_{(-q)}$ with q from 1 to the maximum allowed number of simultaneous devices Q (Figure 3).

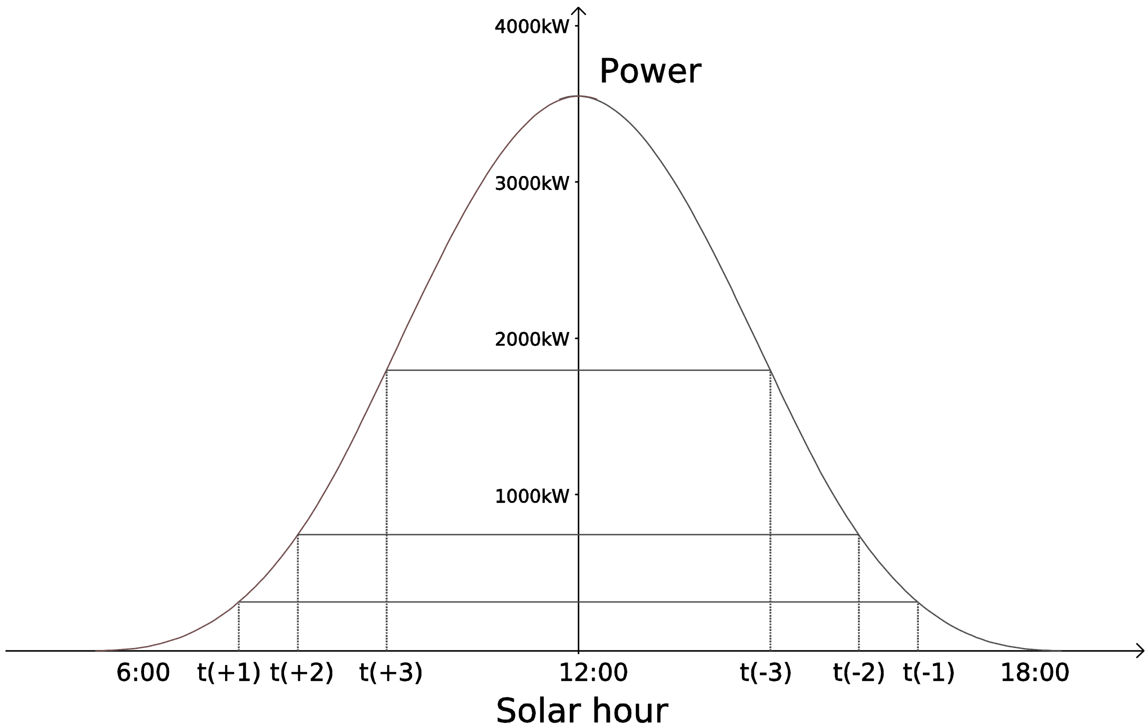

Figure 3. Example of power demand for Q=3 and curve of maximum power supply.

From equations (6) and (16):

$$\frac{\pi_{(1)}}{E\left(t_{(\pm 1)}\right)} = \frac{\pi_{(2)}}{E\left(t_{(\pm 2)}\right)} = \cdots = \frac{\pi_{(Q)}}{E\left(t_{(\pm Q)}\right)} = \eta. \qquad (18)$$

This implies that:

$$t_{(\pm q)} = E^{-1}\left(\frac{\pi_{(q)}}{\pi_{(Q)}} \cdot E\left(t_{(\pm Q)}\right)\right). \qquad (19)$$

As the total time of working for each device is fixed, any modification of its connection time is got diminishing the number of connected devices from q to q-1 at this moment. Considering the symmetry of the power curve, $t_{(+q)} = -t_{(-q)}$, and expression (4) takes the form:

$$T = \sum_q \left(t_{(-q)} - t_{(+q)}\right) = 2 \cdot \sum_q t_{(-q)} \, . \qquad (20)$$

Now, the problem is equivalent to obtaining the solution of the following equation, valid from noon to sunset.

$$E^{-1}\left(\frac{\pi_{(1)}}{\pi_{(Q)}} \cdot E\left(t_{(-Q)}\right)\right) + \cdots + E^{-1}\left(\frac{\pi_{(Q-1)}}{\pi_{(Q)}} \cdot E\left(t_{(-Q)}\right)\right) + t_{(-Q)} = \frac{T}{2} \qquad (21)$$

For the clear sky model derived from equation (13), the solution can be obtained through an analytic expression given by:

$$arccos\left(\frac{\frac{\pi_{(1)}}{\pi_{(Q)}} \cdot E\left(t_{(-Q)}\right) - B}{A}\right) + \cdots + arccos\left(\frac{\frac{\pi_{(Q-1)}}{\pi_{(Q)}} \cdot E\left(t_{(-Q)}\right) - B}{A}\right) + t_{(-Q)} = \frac{T}{2}. \qquad (22)$$

We calculate the parameters A and B from equation (13).

In the general case, the equation (21) can be solved using by example a Newton-Raphson approach. This solution can be applied to solve the problem of scheduling the pump connection time presented in [26] in a numerical, faster and exact form.

2.5. Pseudocode

The algorithm to calculate the optimum size for the PV installation is based on the developments and equations presented before. In a short exposition:

Equation (16) states for the main result of the algorithm. The relation between the available and required power must be constant in all the critical times, corresponding with the connection and disconnection moments as Figure 3 illustrates.

Equation (4) represents the constraint corresponding with the total working time of the installation.

Equation (6) introduces the expression for calculating the number of required panels at any time. Using it in equation (16) derives in equations (18) and (19).

Finally, equation (21) is obtained from the equations (4) and (19) and represents the expression that resumes the optimization problem as a non-linear equation that can be solved for different irradiance models, as it is done, by example, in equation (22).

The pseudocode corresponding to the algorithm is the following:

Algorithm 1 Optimize installation scheduling and size

Input:
Q: Number of maximum simultaneous devices,
$\pi_q(i)$: Power consumption of each allowed configuration i of q devices,
T: Total work time of the installation
Output:
$t_{(-1)}, .., t_{(-Q)}$: Disconnection times,
N_{opt}: Number of pannels
procedure OptimizeInstallation
  for q from 1 to Q **do**
    $\pi_{(q)} \leftarrow min(\pi_q(i))$ ▷ Minimum power of q devices
  /*Solve nonlinear equation*/
  $t_{(-Q)} \leftarrow Root(\sum_{k=1}^{Q-1} E^{-1}(\pi_{(k)}/\pi_{(Q)} * E(x)) + x - T/2 = 0)$
  $N_{opt} \leftarrow E(t_{(-Q)})/\pi_{(Q)}$ ▷ Calculate Nopt
  for i from 1 to $Q-1$ **do**
    $t_{(-i)} \leftarrow E^{-1}(\pi_i/N_{opt})$ ▷ Calculate disconnection time t_i
  return $t_{(-1)}, .., t_{(-Q)}, N_{opt}$

Figure 4. Flowchart Optimization process.

3. CASE STUDY

Figure 5 shows the Albamix network layout, located in Comunidad Valenciana. This PIN comprises 132 nodes and 4.05 km of PVC pipes. It supplies water to 167.7 ha to irrigate orchards containing different varieties of citrus fruit. The minimum service pressure required is $\left(\frac{P}{\gamma}\right)_{threshold}$ = 25 meters of the water column. We grouped the irrigation networks into five segments. The water demands for each segment were around 80-85 L/s. The irrigation management system is a central system scheduled delivery and the total irrigation time presents monthly variation. We recover meteorological information to calculate water demands. We compute the reference crop evapotranspiration using the Penman-Monteith method. The irrigation time values are shown in Table 2.

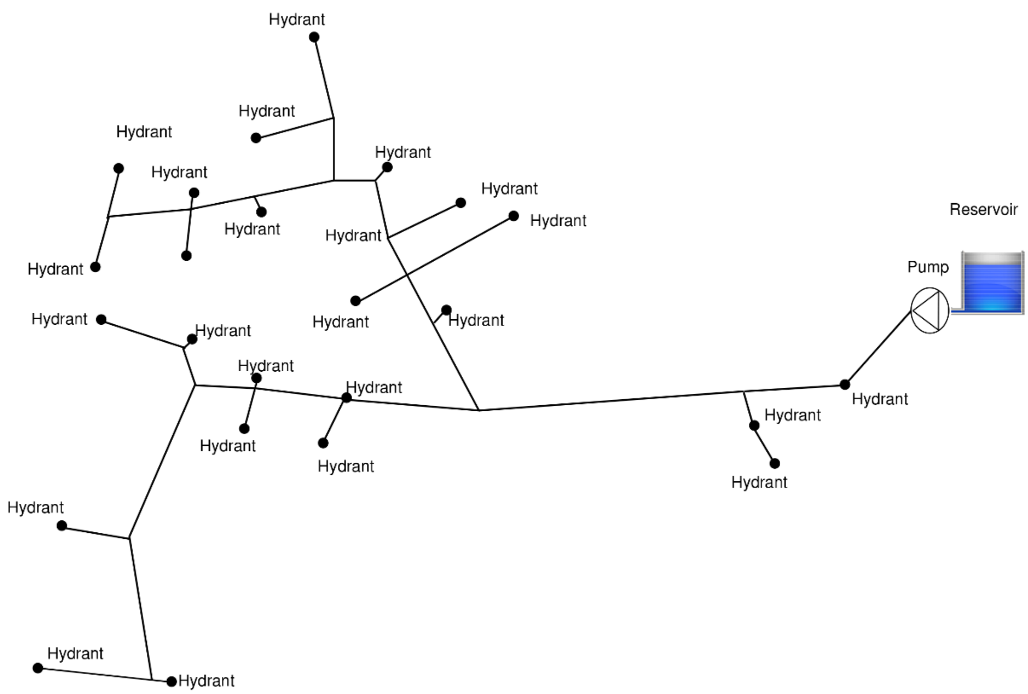

Figure 5. General Layout of the PIN.

Month	January	February	March	April	May	June
Irr. time (h)	0.52	0.69	1.12	1.29	1.93	2.92
Month	**July**	**August**	**September**	**October**	**November**	**December**
Irr. time (h)	3.25	2.70	1.62	0.75	0.43	0.30

Table2. Monthly irrigation time in Albamix network.

In July (the month with the highest water requirements), every segment should be irrigated for 3.25 h/day (Table 2). The network features are incorporated into a hydraulic simulation software such as EPAnet (Rossman, 2000) which represents reality. The energy consumption in pumps and nodes (Pardo et al., 2013) are calculated using UAEnergy (M.A. Pardo et al., 2019).

3.1. Practical restrictions

The utility manager operates a PIN dimensioned for delivering water during nights to exploit low electricity tariffs. Solar irradiance produces energy, but the irrigation time decreases. In local conditions, the number of hours in which it produces photovoltaic energy can be 9h and according to the values showed in Table 2 and the number of segments, the irrigation time is 3.25*5 = 16.25h.

.Given that irrigation time is lower, higher flow rates and higher headlosses owing to friction in the pipes are likely. We defined the upper and lower network flowrate threshold ($Q_{up,th}$=194.9 l/s, $Q_{low,th}$=152.5 l/s) as the highest flowrate injected maintaining the pressure above the standards and the least injected flow not meeting pressure requirements (M A Pardo et al., 2019). The flowrate availability is another constraint. It is the maximum flow rate that can be delivered. If the injected flow is lower than the flowrate availability, no limitation arises in our optimisation problem.

The working time is 9 hours in the month with higher irradiance (July) in these latitudes as a consequence of the technical characteristics of the inverter.

3.2. Seasonal variation

Many considerations regulate power management in PV modules (tilt angle, latitude, azimuth, temperature, etc.). Seasonal variation is a well-known fact, the smallest solar irradiation level occurs in winter while the highest in summer (Bou-Rabee and Sulaiman, 2015; Osinowo et al., 2015; Pardo et al., 2020a) in these latitudes.

On the other hand, water and energy demands are higher during summer and this period coincides with greater energy production. The utility manager must conduct a hydraulic test (considering the network details) to choose the most adverse month. The PV modules must be sized for the worst month (the month selected to size the system). In this month, the pump can operate enough hours to guarantee crops irrigation.

4. RESULTS AND DISCUSSION

4.1. Energy production variation

We figured out the monthly energy production and consumption to establish July as the most unfavourable month (M A Pardo et al., 2019). July has the smallest rate between solar radiation and water needs, which does not coincide with works in urban WPN (Pardo et al., 2020a) in which low values of irradiance in December are more important than water consumption.

4.2. Energy consumption by segment

As an example of the application of equations (21) and (22), let us consider the data corresponding to the problem presented in (Pardo et al., 2018), where the working power for each combination of devices is represented in Table 3:

Combination	**1**	**2**	**3**	**4**	**5**	**1+2**	**1+3**	**1+4**
Power	5.24	5.20	5.26	5.25	5.18	8.41	8.42	8.42
Combination	**1+5**	**2+3**	**2+4**	**2+5**	**3+4**	**3+5**	**4+5**	
Power	8.40	8.41	8.41	8.39	8.43	8.41	8.40	

Table 3: Required power for the combination of each device.

As every segment injects approximately around 80-85 L/s, and the higher and the upper and lower flow rates are ($Q_{up,th}$=194.9 l/s, $Q_{low,th}$=152.5 l/s) (as stated above), we know that as the number of maximum simultaneous devices $Q = 2$ (Figure 5). In short, $Q_{low,th} = 152.5 < 2 * 80 < 194.9 = Q_{up,th}$, and it is not possible to supply three segments as we do not meet the pressure standards.

Dealing with the figures shown in Table 3, segment 5 and the combination 2-5 are the least energy requirements when we feed one or two groups of segments. In short, $\pi_{(1)} = 5.18$ and $\pi_{(Q)} = 8.39$.

4.3. Scheduling and number of PV modules calculation

To calculate the scheduling that minimises the number of photovoltaic panels, we used two irradiance models. The first is a Kasten–Czeplak model where we get A and B from the irradiance data presented in (Pardo et al., 2018). Under the conditions of equal sunset hour angle (ω_s) and total day-generated energy, the irradiance equation takes the form:

$$E(t) = 0.0158997233 \cdot cos(\pi \cdot (t/12 - 1)) + 0.0051107985. \qquad (23)$$

This is a direct-beam method and will serve as a first approach to the result. Then, the scheduling will start and finish with the device 5 and then pass to the combination 2-5. We can fulfil other slides with any of the possibilities offered that the required power will be much fewer than the power provided by the PV panels.

The question now is to establish the instant of connection and disconnection of these two ‘extreme solutions. We solve equation (22) to calculate variable t_2:

$$\frac{12}{\pi} \cdot arccos\left(\frac{\frac{5.18}{8.39} \cdot \left(0.01590 \cdot cos\left(\pi \cdot (\frac{t_2}{12} - 1)\right) + 0.00511\right) - 0.00511}{0.01590}\right) + t_2 - 12 = \frac{16.25}{2} \qquad (24)$$

The solution is $t_2 = 15.23\ h\ (15{:}14)$, when the power generated by the PV panels is 0.01565 W. We calculate the disconnection time for the single device combination using equation (6) and (16):

$$t_1 = 12 + \frac{12}{\pi} \cdot arccos\left(\frac{\frac{5.18}{8.39} \cdot \left(0.01590 \cdot cos\left(\pi \cdot \left(\frac{15.23}{12} - 1\right)\right) + 0.00511\right) - 0.00511}{0.01590}\right) = 16.89 \qquad (25)$$

Using equation (6) and the condition about the number of panels in each period, the number of panels are:

$$\eta = n(t_2) = \frac{8.39}{0.01565} \approx 537 \qquad (26)$$

We can consider this result as a first approach because of the simplicity and inaccuracy of the selected irradiance model. We will calculate the second result using an irradiance function obtained through a polynomial regression over the numeric data for the panel generated power. We got these numbers with Duffie and Beckman equations (Duffie and Beckman, 2013; Pardo et al., 2018).

$$E(t) = -1.7 \cdot 10^{-19} \cdot t^5 + 7.52 \cdot 10^{-6} \cdot t^4 - 3.6 \cdot 10^{-4} \cdot t^3 + 5.64 \cdot 10^{-3} \cdot t^2 - -0.32 \cdot t + 0.058 \quad (27)$$

Now, the equation to solve is:

$$E^{-1}\left(\frac{5.18}{8.39} \cdot E(t_2)\right) + t_2 = \frac{16.25}{2} \quad (28)$$

And the solution is also t_2 =15:29 (15.48h) and the available power is now 0.0146. Now, we compute the disconnection time for segment 5.

$$E^{-1}\left(\frac{5.18}{8.39} \cdot E(15.23)\right) = 16{:}38 \text{ (16.63h)} \quad (29)$$

And the optimum number of panels is:

$$\eta = n(t_2) = \frac{8.39}{0.0146} \approx 577 \quad (30)$$

Optimum scheduling for the polynomial irradiance is displayed in Table 4. We may find that we deliver the same water to plots for every segment (irrigation time for every segment is 3:15 (3.25h)).

Devices	**Connection**	**Disconnection**	**Devices**	**Connection**	**Disconnection**
5	7:21	7:57	1+4	12:00	12:50
2	7:57	8:31	3+4	12:50	13:39
2+5	8:31	9:34	1+3	13:39	14:28
1+4	9:34	10:23	2+5	14:28	15:31
3+4	10:23	11:12	2	15:31	16:05
1+3	11:12	12:00	5	16:05	16:39

Table 4: Required power for the combination of each device.

4.4. Discussion

Converting direct-drive pumping systems (on-grid) into standalone direct pumping photovoltaic system without dealing with the seasonal fluctuation of energy production may contribute to inaccuracies and operation issues. In this analytical procedure, the large-water use is summer is more energy-hungry than the increase in energy production. In other words, this PIN is more sensitive to water consumption than by energy production. We must calculate this for every future case.

The scheduling problem produces better results than those obtained before as we cut down the amount of PV modules (537 and 577) for two different irradiation models. But the key advantage here is not that one, but the quick response of the tool developed to solve this new non-linear equation problem. Authors are aware of the practical restraints indicated here (hydraulics and resource availability) as well as the future functional conditions that may come out at the installation stage. Authors would like to use this tool to consider segments change (in number and water consumption) for some other rigid rotation predetermined scheduled.

To sum up, Table 5 shows the results got solving the scheduling problem.

Irradiance	Trigonometric	Polynomic
$t_{(-1)}$	16:53	16:38
$t_{(-2)}$	15:14	15:29
η	537	577

Table 5: Required power for the combination of each device.

5. CONCLUSION

The sizing of photovoltaic supplier systems is a problem of paramount importance, and if PV is the primary energy source, this point becomes crucial. When the devices (hydrants or units) allow flexibility for connection and disconnection time but maintaining the total consumed energy, we can plan the problem as a scheduling problem. We reduce the problem to a frontier problem where the solution corresponds to the lower power supply curve that includes all the consumption vertexes on the energy-time representation of the best working plan.

The presented method proposes a numeric algorithm solving of a non-linear equation. It is an advance as the genetic algorithm does not guarantee to have the real smallest size for the system.

This issue bears a direct use in pressurised irrigation networks as utility managers can adjust water and energy needs. They can deliver water to crops at every moment of the day. We develop a tool to solve this scheduling problem (Pardo et al., 2020b) using a genetic algorithm, and the result was very time-consuming. Here, we converted this problem into a non-linear equation problem.

But we must recognize several aspects to apply the method to an actual case. First, the accuracy of the results at earlier and later hours depends on the adopted clear sky models for low solar elevation angles. The effect of clouds on the effective irradiance is a complex question because of its stochastic nature. A question opens at this point: Including confidence intervals on irradiance curves, and then in the design of PV installation. The results correspond to the most optimistic configuration to the power supply, an object that can be unreal, a probabilistic analysis to examine the confidence interval of the result might be regarded.

AUTHOR’S CONTRIBUTIONS

All authors contributed equally to this work.

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DATA AVAILABILITY STATEMENT

AIP Publishing believes that all datasets underlying the conclusions of the paper should be available to readers. We encourage authors to deposit their datasets in publicly available repositories (where available and appropriate) or present them in the main manuscript. All research articles must include a data availability statement informing where the data can be found. By data, we mean the minimal dataset that would be necessary to interpret, replicate and build upon the findings reported in the article. The data that support the findings of this study are available from the corresponding author upon reasonable request.

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